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Operations of electric taxis to serve advance reservations by trip chaining: Sensitivity analysis on network size, customer demand and number of charging stations

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ABSTRACT

This research investigated the performance of an Electric Taxi (ET) fleet that catered solely for customers with advance reservations. In a previously related research, a customized Paired Pickup and Delivery Problem with Time Window and Charging Station (PPDPTWCS) had been formulated to solve for the minimum number of taxis that would serve a fixed set of customer demand. The concept behind this fleet optimization was to chain multiple customer trips and trips to Charging Stations (CSs) to form a route and assigned to a taxi driver. In this paper the sensitivity of the ET fleet's operations with respect to network sizes, customer demand densities and number of CSs have been investigated. It also analyzed the market shares of the CSs and the occupancy of a CS over time. The results showed that, (1) the expansion of network size or the increase in customer demand density led to increase in fleet size, number of trips to the CSs and maximum occupancies at the CSs but these performance measures grew at different rates; (2) when the network size and number of CSs were fixed, an increase in customer demand density led to a better utilization of taxis in terms of more customers served per taxi and higher average revenue per taxi; (3) given the same network size and demand density, the ET fleet's performance was relatively insensitive to the number of CSs; and (4) the usage of individual CS was affected by the number of CS and their locations; and (5) when all the ETs were fully charged at the beginning of the same shift hour, they visited the CSs in bunches when their batteries were about to run out. These findings contribute to a better understanding of the operations of the ET fleet and the CSs. They could be used for making better decisions in the planning of ET operations.

Introduction

Taxis play an important role in offering a personalized transportation mode. Taxis that are Elective Vehicles (EVs) are more and more commonly known as Electric Taxis (ETs). The term electric taxi and its acronym ET are used for the rest

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of this article. Cities such as Amsterdam, Bogota, London, Montreal, San Francisco and Shenzhen have been promoting ETs (FleetCarma, 2016).

EVs offer benefits such as zero emission and little engine noise. However, compared to gasoline-powered vehicles that could be refueled quickly, batteries in EVs could not be fully charged in a few minutes. Depending on the battery technology and charging method, an EV's battery may take several hours to be fully charged (Zhou et al., 2015). Because EVs have limited running range before their batteries need to be charged, they are used mainly for inner-city transport, such as the taxi business. There are about 462,000 EVs in the world in 2015 and this figure is forecasted to increase to 41 million by 2040 (Bloomberg, 2016). As for ETs, the world market is expected to grow by 33% per year from 2013 to 2018 (Urban Foresight, 2014). Another forecast has estimated that there will be 260,000 ETs in major cities in the world in year 2020 (EVsRoll, 2012).

The idea of this research came from the taxi operations in Singapore. With the high cost of private vehicle ownership, taxi is a popular transportation mode in Singapore. To compete for customers, all the taxi companies in Singapore equip their taxis with Global Positioning System (GPS) based dispatch systems. There are two categories of taxi reservations in Singapore: current and advance. Current reservations are those in which customers request vacant taxis to reach them within 30 min. Conversely, advance reservations are requests made by customers at least 30 min ahead of pickup times. The focus of this paper is on advance reservations. Gasoline or diesel engines currently power almost all the taxis in Singapore. This research studies the scenario if a taxi company switches its fleet to ETs to serve customers with advance reservations, but faced with the constraints of maximum battery running time and minimum battery charging time.

This research built on an earlier work (Lee et al., 2004) which introduced the Singapore Taxi Advance Reservation (STAR) problem and its solution algorithms. The STAR problem is based on a taxi system with all gasoline-powered vehicles. With the hypothetical scenario of ETs that make up the entire taxi fleet (at least those taxis that are dispatched to serve trips with advance reservations), this problem has been reformulated as the Singapore Taxi Advance Reservation with Electric vehicles (STARE) problem (Wang and Cheu, 2013). The difference between STAR and STARE problems is that in the STARE problem, taxis frequently need to be charged at EV's Changing Stations (CSs). When presenting the STARE problem and its solution algorithm, Wang and Cheu (2013) studied the sensitivity of the ET system's operations with respect to the maximum battery running time, charging time and different number of CSs.

This research continued to focus on the STARE problem and conducted sensitivity analysis with respect to network size, customer demand density and different number of available CSs. It also analyzed the market shares of the CSs and occupancy of a CS over time. Although the investigated problem is inspired by the Singapore's taxi dispatch system, the findings are applicable to any cities that use ETs to serve trips with advance reservations. This research provides taxi system designers and planners insights on how the network size, customer demand, number and location of CSs will impact the system performance of taxi and CS operations. The designers and planners can make use of the findings to make decisions on the service coverage area (network size) and/or number and locations of CSs, when the customer demand fluctuates.

The paper is organized as follows. Following this introduction, a brief description of the existing taxi dispatch system in Singapore is described. The concept of trip chaining is next presented. This is followed by the descriptions of the STAR and STARE problems, and their solution algorithms. The experiments are subsequently presented, which include a comparison of the solutions of the STARE problem with different network sizes, demand densities, number of CSs, market shares and CS occupancy.

Review taxi operations and related research

Taxi dispatch system in Singapore

In Singapore's taxi industry, taxi companies own the vehicles. Each taxi is rented to three drivers who operate in three shifts in a day. The shift hours are fixed, i.e., all the taxis in the company start and end their shifts at the same time. Drivers rent taxis from the companies by paying fixed daily fees. The companies maintain the vehicles but the drivers are responsible for refueling and the cost of the fuel. All the taxis subscribe to, and are part of the company's dispatch system. When a customer requests for a taxi in advance either by phone or by the internet, the company's dispatch center broadcasts the trip information immediately to all the taxis (with and without passenger) in its fleet. It is up to the taxi drivers to decide if they want to bid to serve this customer. Drivers do not have to pay for the bid. The dispatch system assigns this trip to the first driver who bids for it, regardless of the taxi's location. Under this taxi ownership-rental arrangement and dispatch policy, there is no consideration of fleet size and revenue optimization. Taxi companies prefer to increase the number of taxis rented to drivers, as each taxi guarantees a fixed rental revenue per day. In addition, under the existing bidding policy, there is no optimization of the taxi's occupancy rate. That is, up to 100 different taxis might be dispatched to fulfill an equal number of customers. It is up to the taxi drivers to plan their activities within a shift to earn fare revenue.

There are two types of taxi reservation: current and advance. Current reservations are trips that require pickups within 30 min of making the requests. Advanced reservations are trips that are requested by customers more than 30 min ahead of pickup times. The acceptance of an advanced reservation trip usually affects a taxi driver's behavior in serving customers (at the time window before the committed pickup time). A taxi driver often faces a dilemma when the time is approaching for him/her to pick up a customer who has made an advance reservation. If the driver picks up a street hailing passenger, he/she may not be at the pickup location in time to fulfill the advance reservation. On the other hand, giving up the street pickup business becomes an opportunity cost for him/her. This excuse has been used by taxi companies to justify why the advance reservation fee (8.00 Singapore Dollars or SGD) is higher than that of the current reservation (2.30 SGD during off-peak period and 3.30 SGD during peak period) which is contrary to the practice of the hotel, airlines, and car rental industries.

The above-mentioned problems, from the system and driver's points of view, are partly due to the inability of the existing taxi dispatch systems to make full use of customers' advance reservation information. Therefore, two improved taxi dispatch systems that encourage advance reservations and make better use of this information for fleet optimization has been proposed (Lee et al., 2004; Wang and Cheu, 2013). The proposed dispatch systems make use of the concept of trip chaining which is briefly presented in the next sub-section. The key difference between the two improved systems lies in the taxi vehicles: the STAR system uses conventional gasoline-powered vehicles while the STARE system uses ETs. Before describing the STAR and STARE problems, the concept of trip chaining is described in the next sub-section.

Trip chaining

Based on the data provided by taxi companies in Singapore, approximately 3000 advance reservations are made during the daytime (from 8:00 a.m. to 6:00 p.m. on a typical weekday). To take full advantage of the advance reservation information such as the origin, destination, and pickup time of each trip, several trips may be chained form a "route" and offered to a taxi driver as a package. This means that several reserved trips with spatial and temporal distributions of customer requests may be linked, provided that (i) each pickup point is within close proximity to the previous drop-off location; and (ii) the pickup time for the next customer must be later, but not too late than the estimated drop-off time of the previous customer. This will help the driver to minimize his/her vacant time (cruising around in search of roadside customers), as most of his/her time will be spent carrying passengers on board and generating fare revenue. With this more efficient dispatch system, taxi companies may lower its advance reservation fee to encourage even more customers to make advanced reservations. Thus, a smaller taxi fleet may be able to fulfill the same set of trip demand. For the taxi company, the reduction in daily rental revenue may be compensated by restructuring the rental fee, e.g., increase the rental fee for drivers who specialize in serving trips with advance reservations. For taxi drivers, the revenue collected from the chained trips should be more than enough to cover the reduction in the advance reservation fee, after paying for the taxi rental. The CSs may be owned by the taxi company or a third entity. The cost of charging EV may be the paid by the taxi company (to the CS owner by a fixed monthly fee or by fixed rate per charge) or by the taxi drivers to the CS owner. Details of the business model is not within the scope of this article.

The STAR problem

This section describes the STAR problem that forms the foundation of the STARE problem. The STAR problem may be described (in the context of Pickup and Delivery Problem with Time Windows, or PDPTW) as follows:

- Multiple vehicles (taxis) are available all over the street network instead of starting from a central depot and return to a central depot. That is, a chained route starts from the pickup point of the first customer and ends at the drop-off point of the last customer.
- Pickup and delivery (drop-off) are paired and directly connected without any interruption from other pickup or delivery. That is, a pickup must be followed by a drop-off, followed by another pickup and then a drop-off, and so on. In this way, a taxi serves up to only one customer at any time.
- Hard and extremely narrow-time window, i.e., a desired pickup time with minimum deviation (flexibility). Usually, when making an advance reservation, a customer requests a desired pickup time. A customer will complain if he/she is forced to wait for more than a few minutes beyond the requested pickup time.
- The customers automatically respect the vehicle (taxi) capacity constraint. In real life, a customer will obey this constraint when specifying the number of taxis to be reserved. Multiple taxis in one reservation are treated as multiple vehicle trips with the same pickup and drop-off locations, and time window. In other words, they are treated as multiple reservations, with one taxi per reservation.
- Short solution time. After submitting an advance reservation request, a customer usually expects to receive a confirmation (by phone call, text message, email or notification in smartphone application) in less than five minutes that contain information such as the taxi's license plate number, driver's name, pickup time and location.

The STARE problem

In this research, we assume that the taxi fleet consists of only ETs that need frequent charging (and drivers take breaks when their vehicles are being charged). The new scenario is formulated as the STARE problem (Wang and Cheu, 2013). In addition to the conditions as specified in the STAR problem, there are additional constraints caused by the ET's battery capacity:

- All ETs are fully charged at the beginning of a shift.
- All ETs have the same maximum running time. The running time is the time when a vehicle is moving in the network, consuming battery power. This includes time carrying customers from their pickup to the drop-off locations, time driving without passenger between the last drop-off and the next pickup locations, and time driving to and from CSs. The running time does not include idle time, waiting time for the next customer and battery charging time.
- The number and locations of CSs are fixed. The CSs has no capacity constraint.
- Since the CSs have no capacity constraint, ETs arriving at the CSs are served immediately. Each ET spends a fixed charging time at a CS irrespective of the remaining battery power. The charging time is sufficient to charge a battery from zero to full power.

Model formulation

To solve the STARE problem, a Paired Pickup and Delivery Problem with Time Window and Charging Station (PPDPTWCS) has been adopted by (Wang and Cheu, 2013). Before presenting the PPDPTWCS, the Paired Pickup and Delivery Problem with Time Window (PPDPTW) is first described.

The PPDPTW models the situation in which a fleet of vehicles must serve a collection of transportation requests. Each request specifies a pair of pickup and delivery locations, each with a time window. Vehicles must perform a pickup, followed by a delivery, and then another pickup and delivery, and so on. The vehicles must be routed to serve all the requests, satisfying time windows and vehicle capacity constraints while optimizing an objective.

In PPDPTWCS, an ET needs to go to a CS when its battery is about to be depleted. The trip to a CS is modeled as a paired pickup and delivery requests to be performed the same location (the CS), with the trip time between the pickup and delivery (stationary at the CS) equal to the battery changing time. The CS location is not pre-determined. It is the nearest CS after the last customer's drop-off point. The time window for the pickup (arrival time at a CS) is determined by the estimated remaining battery power after serving several customer pickup and delivery jobs. There is no time window for the delivery at the CS. Moreover, there is no battery consumption when an ET is at a CS; instead the battery is being charged. The objective of the PPDPTWCS is to minimize the number of chained routes, which is equivalent to minimize the ET fleet. Details of the mathematical formulation can be found in Wang and Cheu (2013).

Solution algorithm

As PPDPTWCS is a Non-Polynomial-hard (NP-hard) problem, exact solution of large, real-world problems (such as the STARE problem with thousands of pickups and drop-offs) will be difficult to obtain within reasonable time. Therefore, a two-phase heuristic has been proposed to solve this ET dispatch problem in real-time.

Phase 1 of the heuristic seeks to construct a feasible solution. Based on the earlier research results of the STARE problem (Wang and Cheu, 2013), the earliest time window insertion heuristic was adapted for this phase in all the case studies reported in this paper. The earliest time window insertion heuristic extends a chained route by adding a customer trip if the next customer's pickup time is immediately after the last drop-off time of the existing route. A new route is introduced when no more customers can be added to the current route. The logic of the earliest time window insertion heuristic is an iterative approach with the following steps:

1. Let all the taxis have empty routes.
2. Let L be the list of unassigned advance reservations.
3. Take a reservation v which has the earliest pickup time in L.
4. Insert v into a route at a feasible position if v satisfies the constraints of pickup and drop-off times. Otherwise, assign v to a new route. Remove v from L.
5. Check the battery status of all routes. A trip to a CS may be inserted.
6. If L is not empty, go to step 3; otherwise, assign one route to a taxi.

The initial feasible solution is then improved in phase 2.

Phase 2 of the heuristic attempts to improve the solution obtained in phase 1. In this phase, two types of moves, namely exchange and relocate (customer trips between two routes), are combined with the Tabu search technique. An exchange operation swaps customer trips between two routes, whereas in a relocation operation, a customer trip is removed from its original route, inserted into another route or reinserted into the same route but at a different position. To avoid the search from revisiting an earlier solution, the Tabu search technique is introduced. A Tabu list records the previous moves performed. A potential move is considered Tabu (and prohibited) if it is in the Tabu list. This ensures that previously visited solutions will not be repeated.

More details of the two-phase heuristics can be found in Wang and Cheu (2013).

Related research on electric taxis

Factors that influence the operations of an ET fleet, as opposed to gasoline-powered taxis include the number of CSs, locations of the CSs, capacity of each CS, battery's maximum running time (at full charge), battery charging time (from empty to full), and ET-CS assignment policy. As the market of commercialized ET fleet is still relatively new, only a handful of research have been conducted on the impacts of these factors. They are mostly motivated by implementation issues in China.

Zou et al. (2016) studied the operations of a fleet of ETs used in a demonstration project in Beijing, and found that: (i) the average driving distance per taxi per day was 112 km; (ii) 92% of the ETs charged their batteries twice a day; and (iii) the two trips to the CSs coincided with the peak traffic periods in the morning and evening. In a separate study, Li et al. (2015) found that ETs in Shenzhen, China spent on average four minutes to find a CS, and queued at the CS for 15 min before being charged. Both research revealed the loss of taxi's productivity while going to a CS during peak customer demand periods and the congestion problem at the CSs. Bunching of ET arrivals at the CSs, the number of CSs and capacity of the CSs appeared to be major issues in ET operations.

The uneven spatial distributions of charging demand of ETs in major cities in China have created congestion and under-utilization of certain CSs. Niu and Zhang (2015) proposed a charging guidance model to assign ETs to CSs in order to evenly distribute the changing load. Particle Swarm Optimization (PSO) algorithm was used to solve the ET-CS assignment problem. The model was able to evenly distribute ETs spatially when tested in a simulation experiment which used the actual ET data of Shenzhen.

An improved version of the ET-CS assignment model was proposed by Yang et al. (2015) who formulated a multi-objective coordinated charging strategy to maximize the utilization of CSs, minimize the unbalance load imposed on the electric grid (by spatially distributing the ETs) and minimize the taxi's operating cost. Fuzzy mathematics was used to transform the multiple objectives into a single objective function and the problem was solved by the PSO algorithm. The ET-CS assignment strategy was also tested in simulation experiments using the ET data of Shenzhen.

Li et al. (2015) developed an Optimal CS Deployment (OCSD) framework which takes into consideration the historical ET trajectory data, road map data, existing CS locations and CS capacities as inputs. The framework first performs optimal ET-CS assignment followed by optimal charging stall assignment (within a CS). The objective was to minimize the average time for an ET to travel to a CS, and to minimize the average waiting time at the CS. The problem was formulated as an integer programming problem and was solved by the polynomial time approximation algorithm with provable error bound. The OCSD framework was tested in a simulation experiment based on one-month of real ET data of Shenzhen. When compared to real historical data, the simulated results showed that a 26% to 94% reduction in average travel time to a CS, and up to 83% reduction in average waiting time at a CS could be achieved.

None of the above studies investigated the sensitivity of the ET fleet performance with respect to its operating parameters.

Wang and Cheu (2013) introduced the STARE problem and its two-phase solution algorithm. They investigated (i) three different heuristics to find a feasible solution in phase 1; (ii) the impacts of battery technology (maximum running time and charging time) and (iii) the impacts of different number of CSs. The system level performance was analyzed in terms of number of routes or taxis, number of visits to the CSs, average taxi running time and average revenue per taxi. They concluded that the earliest time window insertion heuristics provided the solutions with the least number of taxis to serve all the customers. Longer maximum running time before charging and longer charging time will result in better overall performance (in terms of a smaller taxi fleet to serve all the customers, fewer visits to the CSs and higher average revenue per taxi). They suggested that the impact of network size and demand density be studied in a follow-up research. Therefore, this research conducted the sensitivity analysis of the ET system performance with different network sizes, customer demand densities and in addition analyzed in detail the operations of CSs with different number of CSs.

Li and Huang (2015) presented an optimization model to locate CSs along an interstate highway network to serve EVs between cities. They called it Multipath Refueling Location Model (MPRLM). This is a mixed-integer linear programming model. It is solved by the greedy heuristic algorithm. The model has been applied to find the optimal locations of CSs in the State of North Carolina, U.S. The MPRLM is formulated for privately and commercially owned EVs for intercity trips, with a different objective and did not consider trip chaining. However, they performed sensitivity analysis on the network size and cost of CSs, which motivated this research.

Sensitivity analysis

Background of case studies

This sub-section describes the simulated network, CSs, demands and performance measures that were used in the case studies for the STARE problem.

The Central Business District (CBD) area in Singapore, which is bounded by the Electronic Road Pricing (ERP) gantries, was used as the network in this research. A microscopic simulation tool, PARAMICS (Quadstone, 2009), was used to model the CBD network which generated link travel times for the case studies. Fig. 1 provides a screen shot of the CBD network coded in PARAMICS and the locations of the eight candidate CSs. These simulated travel times were later used to construct the

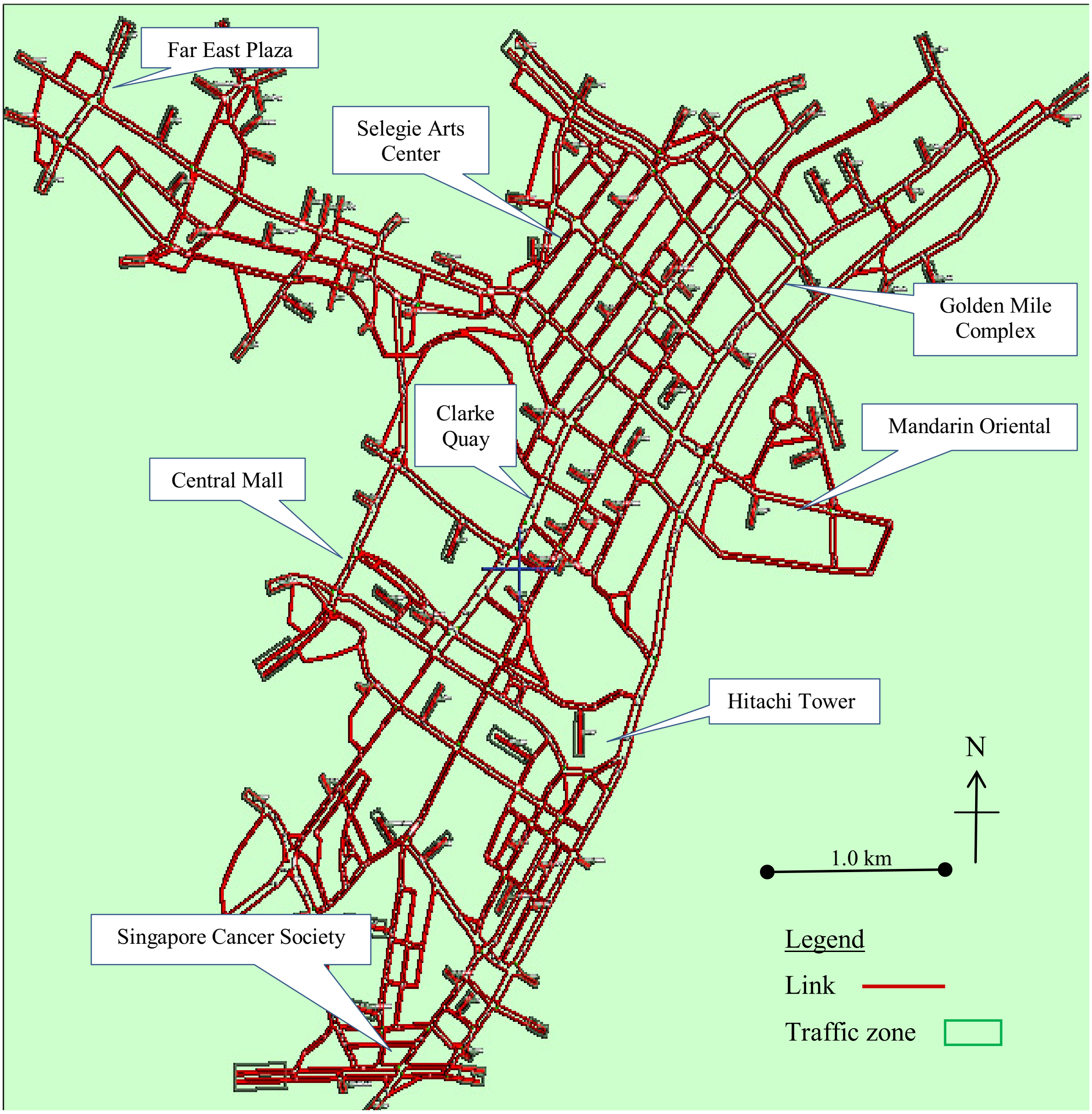

Fig. 1. Simulated network and candidate charging stations.

time-dependent link-to-link travel times between each pickup and drop-off locations, between the previous drop-off and the next pickup locations, between the last drop-off location to a CS, and from a CS to the next pickup location. Details of the traffic simulation model were the same as Lee et al. (2004). Therefore, they are not described here.

As there are ERP gantries to separate the CBD area from other parts of Singapore, it was assumed that a fleet of ETs always does their business within the CBD to avoid the ERP toll. Based on the data provided by taxi companies in Singapore, approximately 3000 advance reservations were made during the day time (from 8:00 a.m. to 6:00 p.m.) across the whole island of Singapore. We assumed that up to one-third or 1000 of such trips had pickup and drop-off locations all within the CBD area.

The 1000 pairs of taxi pickup and drop-off locations were randomly generated from 100 major trip generators (e.g., major office buildings, shopping malls, hospitals, hotels and convention centers) within the CBD. The pickup times of the trips were randomly generated from 8:00 a.m. to 6:00 p.m. This 10-h period was equivalent to one of the three taxi drivers' work shift in a day. A sample of the origin, destination and requested pickup time for each trip in a demand set can be found in Wang and Cheu (2013).

Table 1
Design scenarios for case studies.

Case	Parameter to analyze	Network size	Demand (trips)	No. of charging stations
1	Network size	2 times 4 times 8 times	1000	4 [Far East Plaza, Hitachi Tower, Central Mall, Golden Mile Complex]
2	Demand	4 times	250 500 1000	4 [Far East Plaza, Hitachi Tower, Central Mall, Golden Mile Complex]
3	No. of charging stations	4 times	1000	2 [Far East Plaza, Hitachi Tower] 4 [Far East Plaza, Hitachi Tower, Central Mall, Golden Mile Complex] 8 [All locations in Fig. 1]
4a	Max. occupancy of charging stations	2 times 4 times 8 times	1000	2 [Far East Plaza, Hitachi Tower]
4b	Max. occupancy of charging stations	4 times	250 500 1000	2 [Far East Plaza, Hitachi Tower]
4c	Max. occupancy of charging stations	2 times 4 times 8 times	1000	4 [Far East Plaza, Hitachi Tower, Central Mall, Golden Mile Complex]
4d	Max. occupancy of charging stations	4 times	250 500 1000	4 [Far East Plaza, Hitachi Tower, Central Mall, Golden Mile Complex]
5	Number of visits to charging stations	4 times	1000	4 [Far East Plaza, Hitachi Tower, Central Mall, Golden Mile Complex]

For all the case studies presented in this paper, the objective of the STARE problem was to minimize the number of taxis (chained routes) that could serve all the trips.

The battery charging time was set to 45 min and the maximum vehicle running time was set to 135 min. A taxi was fully charged at the beginning of a route or a shift. Table 1 summarizes the design scenarios of the five case studies reported in this paper.

The performance measures analyzed were:

- Total number of trips to the CSs. This is the total number times ETs went to the CSs to charge their batteries. An ET may be charged multiple times in a shift. For example, if an ET is charged three times, it is counted as three trips to the CSs. This measure reflects, at the system level, the cost and level of disruptions caused by charging batteries between trips that serve customers.
- Average number of trips to the CSs. This is the average number of trips made by an ET to CSs per shift. It is an indicator of the cost of charging and the opportunity cost of not serving customers to generate revenue.
- Maximum occupancy at CSs. This measure collect statistics on the maximum number of ETs being charged at the same time at the most congested CS. This may be used by the taxi company to decide the number of stalls to rent at individual CS, or for the owners of CSs to decide the capacity of the most congested CS.
- Fleet size. This is the minimum number of ETs that are needed to serve all the customer trips with advance reservations. Each ET is assigned a chained route to pick up and drop off several customers. The fleet size is the same as the number of routes in the solutions.
- Total fleet travel time. This is the running time of all the ETs, excluding the waiting time, idle time and charging time. It includes the time ETs carrying customers from pickup to drop-off locations, the travel times between the previous drop-off and the next pickup locations, and the travel times to and from CSs. The total fleet travel time is an indicator of the total energy consumption as well as the contribution of the taxi fleet to network congestion.
- Average travel time per taxi. This is the total fleet travel time divided by the fleet size. It is the time an average driver spends driving on the road.
- Average revenue per taxi. The average revenue is the total fleet revenue divided by the fleet size, to represent the average income of a taxi driver during the shift. The revenue per customer trip was based on the taxi fare of ComfortDelgro, the largest taxi company in Singapore. Each customer trip generated revenue according to the year 2013 fare schedule: 8.00 SGD of advance reservation fee, 3.00 SGD for the first km, 0.22 SGD per 400 m up to 10 km, followed by 0.22 SGD per 340 m after 10 km (ComfortDelgro, 2013). Note that, since the total customer demand in a shift is fixed, the total fleet revenue is constant irrespective of the number of taxis used.

Table 2 lists the performance measures and the stakeholders (taxi company, driver and CS owner) who are interested in these performance measures.

Table 2
Performance measures and stakeholders.

Performance measure (unit)	Stakeholder	Application of the measures
Total number of taxi trips to the CSs (trips)	Owner of CSs	To estimate CS revenue if collect fee per charge
	Taxi company	To estimate the total charging expenses if paid by the company
Average number of trips to CS (trips/taxi)	Taxi drivers	To estimate the average charging cost if paid by the taxi drivers
Maximum occupancy at CSs (taxis)	Owner of CSs	To decide the capacity of each CS; To estimate the stall rental income if rent to the taxi company on permanent basis and not collect fee per charge
	Taxi company	To decide the number of stalls to rent at each CS, if the company rents exclusive stalls for its ETs and not paid per charge
Fleet size (taxis)	Taxi company	To decide on the number of taxis to provide and to project the taxi rental revenue
Total fleet travel time (minutes)	Transportation planners	To estimate the traffic congestion, energy consumption and pollutants caused by the ETs
Average travel time (minutes/taxi)	Taxi drivers	To estimate the work load per shift
Average revenue ($/taxi)	Taxi drivers	To estimate the income

In each case study, one or two system parameter values were varied in different scenarios while other parameters were kept at constant values. The STARE problem was solved for each of the several scenarios. The STARE problem's solutions consisted of the minimum number of ETs that were able to serve all the customer demands. For each ET, an assigned route contained a series of paired pickups and drop-offs, trips to the CSs, and for each pickup, drop-off and CS the location, arrival and departure times. From these solutions the performance measures were then calculated and compared.

Case study 1: network size

Case study 1 analyzed the effect of network size on STARE's system operations. This was because not all the cities have the same network size or distance between intersections. In this case study, the demand density was fixed at 1000 trips (from 8:00 a.m. to 6:00 p.m.) and the number of CSs was four. The four CSs were at Far East Plaza, Hitachi Tower, Central Mall and Golden Mile Complex. Because the original network was too small to observe the performance measures with different CS locations, this network was not used in all the case studies reported in this paper. Instead, the network size was increased to two, four and then eight times of the original network. The link lengths and hence the link travel times in the original network were multiplied by two, four and eight correspondingly. The 1000 customer origins and destinations remained the same (relative to the positions in the network) regardless of the network size; only the driving distance and driving time had increased.

The numerical results of case study 1 are shown in Table 3. From Table 3, it can be observed that with the expansion of network size, to serve the 1000 customer trips, more taxis are necessary. The increase in fleet size is expected. However, the increments are not linear. When the network size was doubled from two to four and then doubled again to eight times of the original size, the fleet size increased by 54% (52–80 taxis) and 86% (80–149 taxis) respectively. The higher increment in fleet size, in absolute number of taxis and in percentage, when the network became bigger was because more taxis were spending time traveling to/from the CSs and spending more time at the CSs. The total number of trips to the CSs and the maximum occupancy at the CSs also increased. The increase in travel time between pickup and drop-off locations led to higher energy consumption, which was reflected in the higher number of trips to the CSs. However, as the fleet size also increased with the network size, the average number of trips to the CSs could either increase or decrease. Due to the increase in driving distance, the total fleet revenue also increased. However, as the fleet size also increased, the average revenue per taxi may not necessarily increase; instead it declined from $322/taxi to $269/taxi, and then to $209/taxi when the network size was increased from two to four and then to eight times of the original size. From this analysis, it appeared that the network size (which may be interpreted as the area served by the ET fleet) should not be too big. There optimal network size and the distance between CSs may be related to the maximum battery running time. This is a possible direction of future research.

Table 3
Results of case study 1.

Network size	Total no. of trips to CSs (trips)	Average no. of trips to CSs (trips/taxi)	Max occupancy at CSs (taxis)	Fleet size (taxis)	Total fleet travel time (minutes)	Average travel time (minutes/taxi)	Average revenue ($/taxi)
2 times	65	1.25	9	52	12,533	241	322
4 times	112	1.40	14	80	22,466	281	269
8 times	199	1.34	20	149	42,579	286	209

Case study 2: demand density

Case study 2 investigated the effect of varying customer demand density when the network size and number of CSs remained the same. This scenario was based on the assumption that when the advanced reservation system was first implemented in a city, the customer demand started at a lower level but grew with time. In this case study, the network of four times the original size was used. There were four CSs (at Far East Plaza, Hitachi Tower, Central Mall and Golden Mile Complex). The demand density was varied from 250, 500 to 1000 customer trips. The 250 and 500 trips were randomly selected among the 1000 origin-destination pairs and the corresponding pickup times.

The numerical results of case study 2 are reported in Table 4. The trends in Table 4 show that a higher trip demand caused the solutions to have a larger fleet size (more routes or taxis used). This generated more total number of trips to the CSs and increased the maximum occupancy at the CSs because the number of CSs remained at four. However, as the demand doubled from 250 trips to 500 trips and then doubled again to 1000 trips, the fleet size did not double. In fact, the fleet size increased by multipliers of 1.5 and 1.9 respectively. As the demand densities (spatially and temporally) became higher, the solution algorithm was able to chain customer trips more efficiently with fewer and shorter empty trips in between. Each taxi was able to serve more customers within the same shift hour. Not shown in Table 4 (but calculated by dividing the demand by fleet size), the average number of customer trips per route or taxi were 8.9, 11.9 and 12.5 trips, for demand densities of 250, 500 and 1000 trips respectively. This increase in efficiency led to the increase in average revenue from $245/taxi, to $269/taxi and then to $280/taxi. The number of trips to the CSs remained at 1.39–1.43, which is relatively insensitive to the trip demand, because more taxis have been deployed to serve customers. From another point of view, each taxi was able to serve more customer trips before going to a CS, thereby contributed to increases in revenue. Using the information listed in the various columns in Table 4, it was calculated that the average number of customers served before a taxi proceeded to a CS were 6.4, 8.3 and 8.9 customer trips, for demand densities of 250, 500 and 1000 trips respectively. The results of this case study showed when the network size and CSs were fixed, there was an economy of scale in the EV taxi service when the demand density increased.

Case study 3: number of charging stations

In case study 3, the effect of using different number of CSs was investigated. This scenario assumed that the taxi company has the flexibility to make contractual arrangement with certain CSs. This case study used the network of four times the size of the original network, demand density of 1000 trips, but with two, four and eight CSs. For the scenario of eight CSs, all the CSs as shown in Fig. 1 were used. For the scenario of four CSs, the four CSs (at Far East Plaza, Hitachi Tower, Central Mall and Golden Mile Complex) located at different parts of the network were selected. For the scenario of two CSs, the selected locations were at Far East Plaza and Hitachi Tower.

From Table 5, it can be seen that since the customer demand density was fixed, more CSs resulted in slightly fewer routes or taxis used, lower total travel time of the fleet (contributed less to traffic congestion), and higher average revenue per taxi. This was because taxis spent less time travel to the nearest CSs and the time saved was used to serve customers. When the number of CSs was doubled, although the total numbers of visits to the CSs remained at the same level (as expected), between 111 and 114 trips, the maximum occupancy at the CSs dropped significantly. The reductions were less than 50%, at 33% (from 21 to 14 taxis) and 21% (from 14 to 11 taxis) when the number of CSs was doubled from 2 to 4, and then doubled again from 4 to 8. The average revenue per taxi also increased but only marginally. Overall, other than the maximum occupancy at the CSs, the remaining performance measures were not so sensitive to changes in the number of CSs, compared to case studies 1 and 2 (changes in network size and demand density). Still, more CSs resulted in a slightly more efficient system. The results of this case study indicated that more CSs did not bring economic benefit to the taxi company. The taxi company may have to bear the cost of having more CSs, and yet there will be fewer routes or taxis used (which means less daily vehicle rental revenue). The taxi company may want to consider using a different vehicle rental policy with the drivers, and the charging fee. Then, it may be possible to weight the trade-off between the cost of having more CSs and the benefit this could bring. This could be another direction of future research.

Case study 4: market shares of charging stations

Case study 4 investigated the market shares of the CSs and the temporal occupancy of a CS. This case study was divided into 4 parts. The scenarios are listed in Table 6. Case studies 4a and 4b used only two CSs (at Far East Plaza and Hitachi

Table 4
Results of case study 2.

Demand (trips)	Total no. of trips to CSs (trips)	Average no. of trips to CSs (trips/taxi)	Max occupancy at CSs (taxis)	Fleet size (taxis)	Total fleet travel time (minutes)	Average travel time (minutes/taxi)	Average revenue ($/taxi)
250	39	1.39	5	28	7532	269	226
500	60	1.43	9	42	11,709	279	254
1000	112	1.40	14	80	22,466	281	269

Table 5
Results of case study 3.

No. of charging stations	Total no. of trips to CSs (trips)	Average no. of trips to CSs (trips/taxi)	Max occupancy at CSs (taxis)	Fleet size (taxi)	Total fleet travel time (minutes)	Average travel time (minutes/taxi)	Average revenue ($/taxi)
2	111	1.26	21	88	23,101	263	245
4	112	1.40	14	80	22,466	281	269
8	114	1.48	11	77	21,910	285	280

Table 6
Results of case study 4.

Case	No. of CSs	Network size	Demand (trips)	Charging station, CS	Total no. of trips to CSs (trips)	Max. occupancy at CSs (taxis)
4a	2	2 times	1000	Far East Plaza	18	5
				Hitachi Tower	52	13
		4 times		Far East Plaza	27	8
				Hitachi Tower	84	21
		8 times		Far East Plaza	49	11
				Hitachi Tower	144	29
4b	2	4 times	250	Far East Plaza	6	3
				Hitachi Tower	34	8
			500	Far East Plaza	11	5
				Hitachi Tower	52	12
			1000	Far East Plaza	27	8
				Hitachi Tower	84	21
4c	4	2 times	1000	Far East Plaza	18	5
				Hitachi Tower	0	0
				Central Mall	29	9
				Golden Mile Complex	18	6
		4 times		Far East Plaza	25	6
				Hitachi Tower	0	0
				Central Mall	44	12
				Golden Mile Complex	43	14
		8 times		Far East Plaza	51	11
				Hitachi Tower	3	2
				Central Mall	65	16
				Golden Mile Complex	80	20
4d	4	4 times	250	Far East Plaza	7	4
				Hitachi Tower	0	0
				Central Mall	18	5
				Golden Mile Complex	14	5
			500	Far East Plaza	14	4
				Hitachi Tower	0	0
				Central Mall	22	7
				Golden Mile Complex	24	9
			1000	Far East Plaza	25	6
				Hitachi Tower	0	0
				Central Mall	44	12
				Golden Mile Complex	43	14

Tower) while case studies 4c and 4d have four CSs (at Far East Plaza, Hitachi Tower, Central Mall and Golden Mile Complex). In case studies 4a and 4c, the network size was varied from two to four and then to eight times of the original network but the demand density was fixed at 1000 trips. Whereas in case studies 4b and 4d, the network size was fixed at four times the original size but the demand density was varied from 250, 500 to 1000 trips. Some of the scenarios in this case study were the same as in case studies 1 to 3.

In case study 4a, the two CSs had an approximately 25/75 split of trips to the CSs, irrespective of the network size. The station at Hitachi Tower was utilized three times of that of the station at Far East Plaza. This is because Hitachi Tower was at a more central location in the network. As found in case study 1, with a larger network size, more trips to the CSs were made and a higher maximum number of vehicles was observed at the CSs.

In case study 4b, as found in case study 2, double or quadruple the demand density caused a smaller increase in trips to the CSs and the maximum occupancy at the CSs. The CS at Hitachi Tower was utilized three times of that of the CS at Far East Plaza. It is observed that a smaller demand density led to a higher disparity in the market shares between the two CSs.

Since there was imbalance utilization of the two CSs as found in case studies 4a and 4b (with Hitachi Tower having the majority of the market share), the number of CSs was increased to four in case studies 4c and 4d. The four CSs were located at different parts of the network (see Fig. 1). In cases 4c and 4d, contrary to earlier results with 2 CSs, very few taxis were sent to Hitachi Tower to charge their batteries. On the other hand, the CS at Far East Plaza becomes relative well utilized. The results indicated that using three CSs (at Far East Plaza, Central Hall and Golden Mile Complex) might be sufficient. If the taxi company wants to have three or four CSs, it can save infrastructure cost by not having a CS at Hitachi Tower. It was also noticed that as the network increased in size, more trips were made to the CS at Golden Mile Complex.

In case study 4d, Hitachi Tower was not visited by any taxi at all. As the customer demand density increased, more taxis were sent to Central Hall and Golden Mile Complex to be charged. These two CSs have approximately the same total number of visits and maximum occupancies.

The results of this case study have demonstrated that the number and locations of CSs in the network affects their usage. However, the occupancies of CSs are difficult to predict without a network modeling exercise as shown in this case study.

Case study 5: occupancy of charging station over time

In case study 5, the usage of a CS over time from 8:00 a.m. to 6:00 p.m. was examined. This analysis provided a tool for the taxi company or the CS owner to estimate the demand of CS so that they can make the decision on the capacity of the CS. The case analyzed had network size of four times the original size, demand of 1000 trips and four CSs (at Far East Plaza, Hitachi Tower, Central Mall and Golden Mile Complex). The CS at Far East Plaza was selected to illustrate the utilization of a CS during the shift. This case is part of case studies 1, 2, 3, 4c and 4d. The Far East Plaza CS served 25 taxis from 8:00 a.m. to 6:00 p.m. The maximum occupancy at this CS was six taxis and this occurred from 11:30 a.m. to 11:45 a.m.

For this analysis, the chained routes of all the taxis were examined. The arrival and departure times of the taxis at the Far East Plaza CS were extracted. Table 7 shows the arrival times of the 25 visits. It was assumed that once arrived, every taxi immediately occupied a charging stall for 45 min. After that it departed to pick up the next customer or moved to a regular stall while waiting for the time to pick up the next customer.

Since all the taxis were fully charged at the beginning of the shift at 8:00 a.m., and a fully charged taxis had a maximum of 135 min of running time, it was expected that no taxi would visit the CSs in the first two hours. The first taxi arrived at the Far East Plaza CS at time point of 134th minute after 8:00 a.m. (or 10:14 a.m.). This taxi stayed in the first charging stall for 45 min until the 179th minute or 10:59 a.m. The second taxi arrives at time point of 148th minute (or 10:28 a.m.). When this taxi arrived at the CS, the first taxi was still being charged. Therefore, the number of occupied charging stalls increased from one to two. The number of occupied charging stalls continued to increase until the first taxi was fully charged and left.

Fig. 2 plots the occupancy of the Far East Plaza CS at 15-min intervals. The time in the horizontal axis is the clock time when taxi inventory was taken at the CS. From the distribution of occupied charging stalls over time, it can be observed that the taxis arrived at bunches the CS in three different time windows (10:15 a.m. to 12:30 p.m., 1:15 p.m. to 3:15 p.m. and 3:45 p.m. to 5:00 p.m.) when the 135 min of maximum running time of a fully charged battery was almost exhausted. This pattern is consistent with the finding of Zou et al. (2016). In our case studies the CSs were assumed to have no capacity constraint. In practice, this is unlikely to be so. To handle the capacity constraint, once a ET arrives when no charging stall is available, it must wait at a regular parking stall until a fully charged ET departs. There may be a queue of ET waiting to

Table 7
Arrival times and occupancy at Far East Plaza charging station.

Visit no.	Arrival time (minutes, from 8:00 a.m.)	Arrival time (hh:mm)
1	134	10:14 a.m.
2	148	10:28 a.m.
3	156	10:36 a.m.
4	170	10:50 a.m.
5	171	10:51 a.m.
6	172	10:52 a.m.
7	193	11:13 a.m.
8	200	11:20 a.m.
9	211	11:31 a.m.
10	223	11:43 a.m.
11	227	11:47 a.m.
12	363	1:03 p.m.
13	373	1:13 p.m.
14	379	1:19 p.m.
15	395	1:35 p.m.
16	419	1:59 p.m.
17	430	2:10 p.m.
18	435	2:15 p.m.
19	445	2:25 p.m.
20	454	2:34 p.m.
21	465	3:45 p.m.
22	470	3:50 p.m.
23	477	3:57 p.m.
24	485	4:05 p.m.
25	498	4:18 p.m.

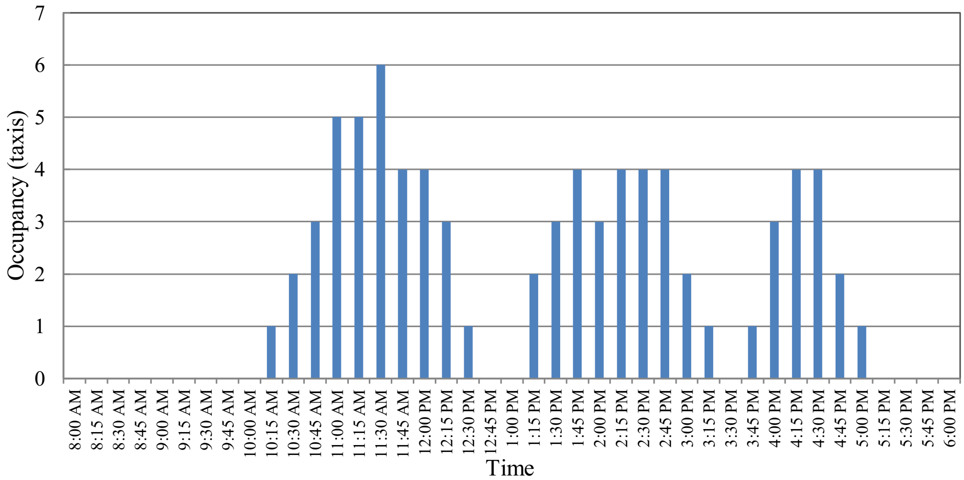

Fig. 2. Occupancy of far East Plaza charging station over time.

be charge. For the STARE problem with CS capacity, the waiting time at a CS may be modeled as a paired pickup and drop-off trip at the CS, with the trip time equal to the calculated waiting time at the CS. This capacitated problem is another possible direction of future research. To avoid congestion at the CSs, it may be necessary for the taxi company to stagger the shift hours (assuming that all the ETs are fully charged at the beginning of their shifts) or pre-schedule the visits to the CSs during the trip chaining process.

From Fig. 2, it was determined that the maximum occupancy at this CS was six and this occurred only once, at 11:30 a.m. Thus, with the tested ET-CS assignment policy, it is not necessary for the taxi company to rent or for the CS owner to build more than six charging stalls at this location. The taxi company may use this analysis technique to determine the number of charging stalls to rent at each CS. The CS owner may also use this technique to determine the capacity each CS.

Conclusions and recommendations for future research

This research has studied the operations of a taxi fleet that used EVs to serve customers with advance reservations. This unique problem has been described as the STARE problem. Given a network with a set of customer demand and CSs, the minimum number of taxi was solved by chaining a few trips to form a route and assigned to a taxi. The impacts of network size, demand density, number of CSs on several system performance measures have been investigated. The market shares of the CSs and occupancy over time at a CS have also been examined. The major findings of this work are:

1. With the increase in network size but with the same number of CSs, more taxis were required to serve the same number of customers. At the system level, the total number of trips to the CSs, maximum occupancy at the CSs and total fleet travel time had increased. At the individual taxi level, the average travel time per taxi increased but the average revenue per taxi suffered a drop.
2. When the network size and the same number of CSs remained the same, more taxis were required to serve more customer trips. There appeared to be economy of scale at the system level when the demand density increased. That is, at the system level, the fleet size and maximum occupancy at the CSs did not increase as fast as the demand density. At the individual taxi level, the average travel time per taxi, number of customers served per taxi and average revenue per taxi increased when there was more demand for taxis.
3. Increasing the number of CSs improved the system's operation. That is, more CSs resulted in fewer taxis used, lower maximum occupancy at the CSs, lower total travel time of the taxi fleet (less energy consumption and traffic congestion). However, the total number of visits to the CSs remained at the same level. At the individual taxi level, the average travel time per taxi and average revenue per taxi increased.
4. The performance measures were more sensitive to the changes in network size and demand density than number of CSs.
5. Not all the CSs were equally utilized. It depended on the number and locations of the CSs, and geographical distribution of customer demand.
6. If the ET were fully charged at the beginning of a shift and they all had the same maximum battery running time, the ET visited the CSs in bunches, when they had almost exhausted their batteries.

The methodology presented in the case studies may help taxi companies to make policy decisions. For example, it may be used by the decision makers to determine the fleet size, number and locations of the CSs, capacity of each CS, and the ET-CS assignment policy.

Assuming that the network size and customer demand are fixed, the idea presented in the case studies may be extended to a bi-level programming model in which the upper level has the objective of optimizing the number, locations and capacities of the CSs, while the lower level solve for the minimum fleet size. In addition, the following potential research directions have been identified:

– Investigate the relationship between the network size (service coverage area) and maximum battery running time;
– Investigate the trade-off between the costs of having more CSs while having fewer ETs to serve the same set of customer demand.

The findings of this research contribute to a better understanding of ET fleet and CS operations for taxi companies, taxi drivers and system designers.

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References

Bloomberg, 2016. Electric vehicles to be 35% of global new car sales by 2040. Bloomberg New Energy Finance, Feb 15, 2016. <http://about.bnef.com/press-releases/electric-vehicles-to-be-35-of-global-new-car-sales-by-2040> (accessed August 1, 2016).
ComfortDelgro, 2013. Comfort CityCab Rates & Charges. Comfort Transportation Pte Ltd and CityCab Pte Ltd. <http://www.cdgtaxi.com.sg/commuters_services_rates.mvn> (accessed July 1, 2013).
EVsRoll, 2012. Electric taxis. EVsRoll.com. <http://evsroll.com/Electric_Taxis.html> (accessed August 1, 2016).
FleetCarma, 2016. Electric taxis are on their way. FleetCarma, Waterloo, Canada. <http://www.fleetcarma.com/electric-taxis-on-their-way> (accessed August 1, 2016).
Lee, D-H., Wang, H., Cheu, R.L., 2004. Trip-chaining for taxi advance bookings: a strategy to reduce cost of taxi operations. In: The 83rd Annual Meeting of the Transportation Research Board Compendium of Papers CD-ROM.
Li, S., Huang, Y., 2015. Development of electric vehicle charging corridor for South Carolina. Int. J. Transp. Sci. Technol. 4, 4.
Li, Y., Luo, J., Chow, C-Y., Chan, K-L., Ding, Y., Zhang, F., 2015. Growing the charging station network for electric vehicles with trajectory data analytics. In: Proceedings of the IEEE 31st International Conference on Data Engineering (ICDE), pp. 1376–1387.
Niu, L., Zhang, D., 2015. Charging guidance of electric taxis based on adaptive particle swarm optimization. Sci. World J. 2015,, 9. http://dx.doi.org/10.1155/2015/354952 354952.
Quadstone, 2009. Paramics User and Reference Manual, Version 6.6.1. Quadstone Ltd., Edinburgh.
Urban Foresight, 2014. EV city casebook. Urban Foresight Ltd. New Castle upon Tyne, U.K. <https://www.iea.org/topics/transport/subtopics/electricvehiclesinitiative/EVI_2014_Casebook.pdf>.
Wang, H., Cheu, R.L., 2013. Operations of a taxi fleet for advance reservations using electric vehicles and charging stations". Transp. Res. Rec.: J. Transp. Res. Board 2352, 1–10.
Yang, Y., Zhang, W., Niu, L., Jiang, J., 2015. Coordinated charging strategy for electric taxis in temporal and spatial scale. Energies 8, 1256–1272.
Zhou, H., Liu, C., Yang, B., Guan, X., 2015. Optimal dispatch of electric taxis and price making of charging stations using Stackelberg game. In: Proceedings of the 41st Annual Conference of the IEEE Industrial Electronics Society (IECON2015), November 9–12, Yokohama, Japan.
Zou, Y., Wei, S., Sun, F., Hu, X., Shiao, Y., 2016. Large-scale deployment of electric taxis in Beijing: a real-world analysis. Energy 100, 25–39.